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Potential Impacts of Connected-Autonomous Vehicles on
Congestion and Safety: A Look at Austin, Texas

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Abstract

Potential Impacts of Connected-Autonomous Vehicles on Congestion and Safety: A Look at Austin, Texas

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Data is a central component of Connected-Autonomous Vehicle (CAV) systems: the advantages and potential challenges of both vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) CAV data underlie the question of wide scale CAV implementation. This report looks at the potential congestion and safety benefits of a vehicle system highly saturated with CAVs in Austin, Texas. Traffic factors such as capacity, intersection delay, and crash rate are examined with respect to their effect on an urban corridor in Austin. The case study relies almost entirely on collected field data to be used as a comparison against potential CAV advantages. In addition to a presentation of the quantitative benefits of CAVs, an infrastructure placement scheme that maximizes data transmission efficiency is also proposed. The results find that vehicle systems can see large improvements in capacity, intersection delay, and number of crashes, and at a relatively inexpensive cost.

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Introduction

Connected-Autonomous Vehicles (CAVs), also known as “self-driving cars,” are vehicles equipped with technology that allows communication between vehicles and the ability to autonomously drive due to their understanding of the roadway based on input data. The computer onboard a CAV uses radio waves to communicate with other equipped vehicles, to understand their location and trajectory, and to plan the car’s route accordingly. CAVs are projected to have significant impacts on the transportation landscape in the coming years [1]. Already, early semi-autonomous technologies such as parallel parking assistance, emergency brake assistance, and adaptive cruise control are available in modern passenger vehicles. These features may soon be joined by government-mandated vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication systems (collectively, and inclusive of any able communication device, V2X). The AASHTO Connected Vehicle Deployment Coalition envisions a timeline of V2I implementation across 20% of intersections by 2025 and 80% of intersections by 2040 [2].

Typical CAV systems see the primary components as being the CAV and the roadside unit (RSU), which transmits and receives data from CAVs. Federal mandates as of April 2014 state that RSUs weigh less than fifteen pounds, and that they must be capable of being installed on a mast arm or traffic pole, or installed in an adjacent cabinet [3].

Future CAV systems are expected to transmit huge amounts of data between vehicle

and infrastructure. Because of this, it is very important to maximize the efficiency of CAV infrastructure placement. It is possible that MPOs or city planning groups will be footing the bill for CAV infrastructure, and therefore it is necessary to appropriately place RSUs according to transmission reach, but not to the point of oversaturation.

Some of the most important proposed benefits of CAVs are their ability to drastically improve traffic maladies such as congestion, as well as their propensity to improve safety by reducing crashes due to inattention and other causes. Much of the focus and reasoning for implementation remains on the benefits to the driver, but there is also tremendous potential for big data collection and analysis to use for real time traffic operations and to inform mobility planning organization efforts. This paper will look at the role of data in CAV systems, including the extent to which CAV data can make changes or improvements in the fields of planning, operations, and safety.

Additionally, this paper will make a case study for the South Lamar Blvd corridor in Austin, TX, using present-day and future projected vehicle volumes, present-day vehicle travel times, and crashes on the corridor between 2010 and 2016. Based on various CAV benefit rates reported in literature, potential quantitative benefits will be estimated for the corridor. The potential infrastructure placement scheme and cost will be included. Studying the potential impacts of a CAV system on a corridor in Austin localizes the benefits and provides a scale of implementation typically not seen in CAV papers. CAVs will likely make their way into traffic systems slowly, and it may be worth implementing

them at a small scale for early pilot projects. Thus, this paper will provide evidence for benefits at the scale of a potential pilot project.

Justification and Context

The state of Texas contains five of the nation's 15 fastest-growing cities, and as such, Texas is set to be a hotspot for transportation challenges. The US Department of Transportation (USDOT) has already chosen the state of Texas as a testing location for autonomous vehicles, due to its booming population and economy [4]. Texas's growing population, particularly in Austin, has led to problems with vehicle safety: the number of vehicle deaths in Austin increases every year, with a 62% increase from 2014 to 2015. Speculation suggests that low gas prices paired with a strong economy and a population increasing too fast for infrastructure to keep up may be leading to more driving in the city of Austin, and thus, more incidents [5].

While Austin does not see nearly as many traffic incidents as other Texas cities such as Dallas or Houston, it nonetheless does have its fair share of dangerous roadways and intersections. Citing a study by Houston personal injury attorney Brian White, Austin contains four of the most dangerous intersections in the state of Texas [6]. Among these four intersections, there have been a total of 244 crashes resulting in 168 injuries between the years 2012 and 2015.

CAVs have the capability to provide a second pair of eyes for drivers. The vast majority of vehicle crashes are caused by roadway-related factors as opposed to vehicle-condition-related factors [7], and it is thus concluded that the technological advancements of CAVs can help reduce the number of vehicle crashes and deaths

substantially. Crashes caused by distracted driving, speeding, and issues with roadway geometry or visibility, among others, can be reduced through the ability of CAVs to communicate with other vehicles and roadside infrastructure. This, coupled with the vehicle's ability to monitor speed, roadway conditions, and vehicle condition make a compelling argument for the use of CAVs to improve roadway safety.

While safety is an extremely important issue that can be addressed and improved upon via intelligent infrastructure placement, this paper will use collected data to make an argument for congestion improvements. Safety improvements are difficult to quantify in a data-collection setting – data involved in this paper will have been collected by the author or supplied by CAMPO. Neither of these avenues provide proper safety analysis – rather, the data looked at will be in the form of vehicle counts and corridor travel times. It is undoubtedly true that the emergence of CAVs will help reduce vehicle crashes, but this paper will provide no new analysis in that realm besides to repeat the conclusions of other authors.

As far as the case study, this paper will look at the Lamar Boulevard corridor between Treadwell Street and Manchaca Rd in Austin, Texas. Lamar Blvd was chosen because of its status in Austin as a primary north-south arterial within the central city. In central Austin, Lamar serves as a great opportunity for a test bed for CAV technology for the following reasons: 1) it is a high-speed and high-capacity corridor for commute trips, 2) it has several traffic signals which could support CAV infrastructure, and 3) the roadway

segment is consistently identified as a site of extreme congestion, including being found in the top 3 non-highway corridors in TxDOT's list of most congested roadways in the entire state of Texas [8].

CAV infrastructure could vastly improve the Lamar corridor in terms of congestion. This paper will explore what treatments can be made along the roadway and in what allocation scheme to maximize efficiency – both in terms of data transmission and cost. The role of data in CAVs continues to expand as CAV production and testing see further advances. With CAVs nearing market penetration, CAV data has been found to provide opportunities for innovation in planning, operations, and safety. However, there are both technical and non-technical challenges associated with CAV data. This paper will look at previous research in both the opportunities and challenges of CAV data.

Connected Vehicle Data

At the lowest communication level, V2X communications rely heavily on the broadcast of Basic Safety Messages (BSM) within a Vehicular Ad-hoc Network (VANET) [9]. BSMs keep track of indicators from within the vehicle, and their primary purpose is to support safety applications. These messages are broadcasted by each car at an adjustable rate of up to 10 per second [10],[11]. The Society of Automotive Engineers (SAE) has established communication standards for connected vehicles (compiled in specification J2735). These standards define the key aspects of V2X such as the format of messages

to be broadcasted (BSMs), channels and frequency (Dedicated Short Range Communication (DSRC)), and beaconing intervals [10].

There are two types of BSMs, known as BSM I and BSM II [12].

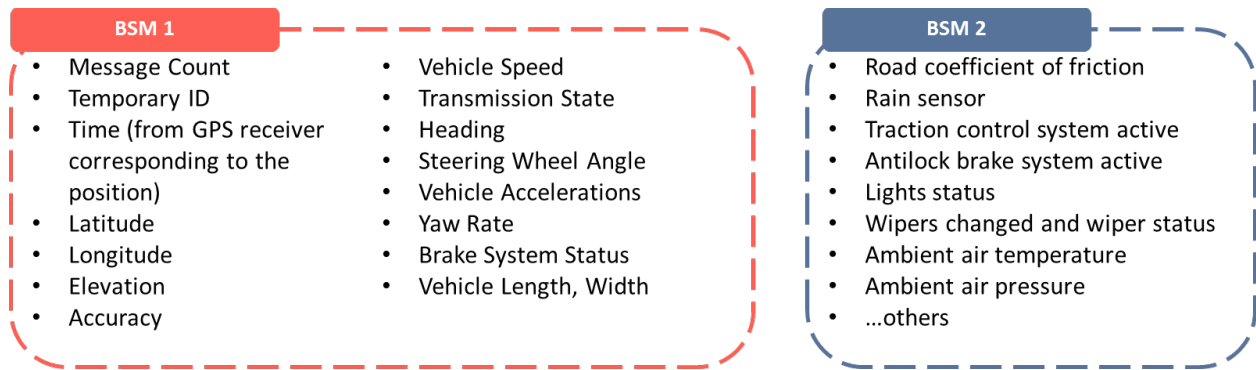


Figure 1: Types of Basic Safety Messages

Messages from BSM I are transmitted up to ten times per second and typically include vehicle status data, such as latitude, longitude, elevation, speed, heading, size of the vehicle, among others. BSM II messages contain additional, non-safety-critical information, such as brake status, lights status, rain sensor, and whether or not systems like antilock brakes and traction control are active. These messages are appended to BSM I messages for broadcasting when a change in the car status or operation occurs.

As contemplated at the earliest levels of implementation, all BSMs are unilateral, broadcasted into the general space (usually traveling a 300m range) for any V2X enabled device to receive. The majority of those receiving devices will use the information in real time and discard old information as new broadcasts are received. This type of data use, known as “data in motion,” negates the need for extensive data storage space and helps

avoid certain privacy concerns, as discussed further below. However, for use beyond real time V2X safety applications, there will need to be storage and transmission of the data to a processing warehouse. This transmission could occur along cellular networks or via roadside collection with a backhaul system connecting the information to the processing warehouse.

As technology advances and on-board computing power increases significantly in concert with a larger number of sensors collecting data, CAVs will likely generate more and more data as time goes on [13]. Currently, the infrastructure needed to appropriately support storing and processing of massive amounts of CAV data is rare, and in the future systems and processes will need to be specifically designed to address these needs.

CAV Data Challenges

To access these advanced applications, the technology capabilities for storage, communication and processing of CAV data must be further developed. Challenges of moving the data from the vehicles and roadside infrastructure to a computer large enough to process and utilize the data begin from the onset. In a situation where hundreds of cars on a short highway stretch are talking to each other and to the roadside infrastructure all at once, there may not be enough space in the DSRC channel for full data sharing, so the first transformation of the data, through some form of data

aggregation, may be necessary. Consider the following example that explains the need for data aggregation, from Pim van der Toolen's 2010 paper:

Assume there is a traffic jam on a highway with five lanes. On every lane, there is a vehicle every 5 meters on a 20 km highway. That is 20,000 vehicles within a 20 km long 5-lane highway. Depending on the supported vehicular application, each vehicle might need to send a huge amount of data every beaconing period. There are, for example, situations where each vehicle might need to send around 1 MB of data each beaconing period. When the transmission range is 250 meters, the number of cars for a 5-lane highway is 250. Moreover, a total of 250 MB needs to be transmitted every beaconing period. That is way too much for today's network dissemination technologies. Currently, vehicles can only send a few kB of data every beaconing period [14].

Van der Toolen summarizes the many proposed data aggregation solutions in his paper. One of these is dynamic grouping [15], which is the idea of grouping similar vehicles and designating a single vehicle out of the group to be the one to transmit data. Security and efficiency are optimized with dynamic grouping, but privacy becomes a concern. Dynamic grouping requires that every vehicle should be able to be identified, including the owner [14].

Another proposed approach is one based on fuzzy logic [16]. A fuzzy logic based approach would allow the vehicle to decide when to aggregate data. A cutoff can be pre-established, and the vehicle can aggregate or not aggregate depending on where a particular indicator is in relation to the cutoff. Van der Toolen's paper gives speed as an

example – where the vehicle aggregates data when driving speeds are low and doesn't aggregate data when driving speeds are high. This results in very high accuracy, but a lot of bandwidth use [14].

Other methods detailed in Van der Toolen's paper include a probabilistic method for hierarchical aggregation [17] that merges different aggregates from a small number of vehicles, a *Catch-up* [18] scheme that looks at time delays between vehicles and then aggregates data if two separate similar messages fall within the same timeframe, cluster-based aggregation [19], and a method that prioritizes security by using fuzzy logic to check whether the data sender is trustworthy enough [20].

Once the data is aggregated in some form, it will need to be transmitted, either via cellular networks or through roadside infrastructure with a backhaul connection to a data warehouse. The type of transmission that occurs here may have further limiting factors that may require more transmission. However, for our purposes, we will assume that the aggregated data from the vehicles will be channeled back to the data warehouse without further modification.

Once the information reaches the data warehouse, storage must be able to handle system wide data and processing must begin in earnest. Nkenyereye et al propose in their 2015 paper [21] a framework to store and analyze CAV big data using Hadoop. Hadoop breaks up data and distributes it across the cluster, which allows large datasets to be analyzed more quickly. The four-step process involves transmitting the vehicle

diagnostics data to a MySQL database, importing that data from MySQL to the data warehouse's Hadoop clusters, and then processing the data to the web server, where it will be manually analyzed. This solution may be able to solve the problem of storing large amounts of CAV data, but it does not address the problem of transmitting CAV data between vehicles and infrastructure.

Non-Technical Challenges

Aside from the technological limitations that come with storing or transferring huge datasets, there are also potential privacy and security concerns. The data generated by CAVs contains information on origin of trip, destination of trip, and location throughout the trip. This data, if accessed by a third party with malicious intent, could be used to track system users and inform criminal activity. As such, there are calls for this data to be scrubbed in some way, to provide anonymity to the driving public. Any scrubbing process would have to be accounted for in the chain of data transfer and likely happen very early in the process. Notably, hacking by third parties may be just part of the concern as many car manufacturers are already receiving and using data collected by their vehicles owned by private parties. This issue provides a strong proxy for analysis of future CAV data use.

In the testimony before the U.S. House of Representatives, Khaliah Barnes of the Electronic Privacy Information Center (EPIC) made the claim that many vehicle manufacturers are vague about how much data their vehicles record, and what they do

with the recorded data. Some manufacturers give the drivers control over the information recorded, allowing them to delete it if desired. However, many manufacturers don't give drivers that ability. Furthermore, some manufacturers only store personal driver information within the car, while many more transmit that information to external locations for storage [22]. Many of those who do send personal information to external locations do not state the purpose of the transmission to a third party. For example, OnStar, the GPS manufacturer, discloses account and vehicle information to unspecified third parties with which OnStar contracts for "joint marketing initiatives," according to their privacy policy [22]. In response to these concerns, legislation was offered by Senator Ed Markey that would mandate cybersecurity measures across all connected vehicles, conspicuous warnings to drivers about the use of their data and provide drivers the opportunity to turn off their data sharing. However, the full senate did not take up this legislation.

Until rules are propagated by a federal agency or governing body regarding CAV data and privacy, there is a layer of uncertainty as to how accessible or valuable the data may be. In CAV test beds, the data was scrubbed to eschew sharing too much data on the drivers, although this occurred after the data was transmitted to the data warehouse. The issue that arises here is the need for balance. Security and privacy should not be sacrificed for overly robust data, but too much scrubbing and security will lower the potential uses of the data.

Existing CAV Data Work: Planning and Operations

Research done by ITS JPO and private and public research organizations has already begun using data generated from CAVs, and this research shows the possibility for future CAV data applications.

For instance, a 2013 ITS JPO report listed off 7 proposed systems that could be enabled through CAV data. These systems, listed below, would require overcoming some of the challenges to be described in this paper, but help begin the conversation as to the significant impacts use of this data could have on real time systems.

- Advanced Traveler Information Systems
- Freight Advanced Traveler Information Systems
- Integrated Dynamic Transit Operations
- Integrated Network Flow Optimization
- Multimodal Intelligent Traffic Signal System
- Response, Emergency Staging
- Communications, Uniform Management and Evacuation
- Road Weather Specific Applications

Regarding planning applications, Eric Paul Dennis et al [23] researched the potential for connected vehicle data to contribute to pavement condition and performance assessment. They found that connected vehicle data could contribute to pavement monitoring in the near term, as well as in the long-term. This includes assessments of pavement structural adequacy, pavement surface distress, pavement ride quality and

serviceability, pavement surface friction, and pavement markings and roadside assets. In order to collect this information, the paper states that only 1% of system user participation is needed to provide adequate pavement condition monitoring.

Jia Hu [24] et al researched connected vehicle data with respect to improving transit signal priority (TSP). According to the authors, current TSP logic is outdated, and buses may not actually benefit from it due to arrival time at the intersection being biased and inaccurately forecasted. They propose that a more sophisticated TSP algorithm is needed to better service a greater proportion of transit buses, and that connected vehicle technology would greatly improve TSP logic. Connected vehicle data contains measurements such as vehicle speeds, positions, arrival rates, rates of acceleration and deceleration, queue lengths, number of passengers, and stopped time – all of which would contribute to a more efficient TSP algorithm. The paper states that according to AASHTO's Connected Vehicle Infrastructure Deployment Analysis, Transit Signal Priority with Connected Vehicle data (TSPCV) is one of the key applications that would enhance mobility [25]. The paper's findings are in agreement with AASHTO's assertion:

When the congestion level is low, TSPCV would help reduce bus delays up to about 90% compared with NTSP under VISSIM simulations. As the congestion level rises, the benefit of TSPCV decreases, while no extra delay is caused. This is because the algorithm is designed to be conditional on person delay [24].

Jing-Quan Li et al's 2013 paper [26] focused on using CAV data on probe vehicles to better estimate queue length in simulation. This advancement will not only serve planning and operations purposes, but research purposes as well. Unlike Songchitruska and Zha's proposal [29], Li et al's paper does not require a significant market penetration rate in order to be effective. Loop detectors have long been the traditional way to collect queue length data, and this paper's proposed method does away with the expensive installation and maintenance costs that come with data collected from loop detectors. At a low penetration rate, the paper recommends fusing data from probe vehicles and loop detectors for better accuracy. However, at a high penetration rate, the data from the loop detector is not needed. Regardless, the CAV data shows its utility in this paper.

Bagheri et al propose in their 2015 paper [27] a way to estimate the saturation flow rate for lane groups at signalized intersections with data from CAVs, rather than fixed dedicated traffic sensors such as loop detectors. The authors found that their method succeeded at estimating temporally varying saturation flow rates to changing network conditions, including lane blockages and queue spillback that limit discharge rates. Their method succeeded even when the market penetration of CAVs is only 20%. The paper does well to show the utility of CAV data in a system with full market penetration, but also states that collection of CAV data is useful even when conventional vehicles outnumber CAVs.

Existing CAV Data Work: Safety

Currently, safety is a focal point of CAV data and the related projections to vastly reduce traffic incidents in a real time situation. However, safety is also affected by long term planning through infrastructure design and installation. Alireza Talebpour et al's 2014 paper [28] discusses using CAV data to better study the effects of near-crash events on safety. With connected vehicle data, the authors were able to study high-risk maneuvers in the entire traffic stream. Previous methods involved using naturalistic driving data and driving simulators, but that method is limited to the number of equipped vehicles in the study. In a scenario where all vehicles are connected via V2I to a TMC, all vehicles will transmit their movement information, leading to fuller data and more accurate analysis. The authors state that the capability to track trajectories in a connected vehicle system provides the opportunity to better identify and predict near crashes – leading to the recognition of unsafe locations along a traffic stream and preventative actions being taken to reduce crash risk. This paper preaches the safety benefits of a connected vehicle system, as the assumptions made in the paper require a fully connected vehicle system to be applicable. Without full market saturation, data on near-crash events will be no better than the naturalistic driving data today.

Signalized intersections of the future could see further improvements in the realm of safety through the use of CAV data. Praprut Songchitruksa and Liteng Zha [29] proposed in their 2014 paper a safety monitoring application that used CAV data to detect

potential safety indicators at signalized intersections, which was then tested in simulation using VISSIM. Among the safety indicators proposed are the frequency of vehicles that run red lights, frequency of conflicts based on maximum deceleration rate, and frequency of rear-end conflicts that are based on minimum time to collision (TTC), among others [29]. The authors developed algorithms for safety applications using V2I data, and tested the simulation with a full market saturation model. The authors found that their proposed safety monitoring framework using CAV data and V2I communications could effectively and successfully detect changes in safety performance in simulation. Since full saturation of CAVs is not expected in the near term, they also found that 50% saturation is required for their algorithm to detect 50% of their safety measures.

Factors Influencing CAV Effectiveness

Collision Avoidance Systems

Many of the safety benefits of CAVs will be due to Collision Avoidance Systems (CAS). CAS technology is not defined as a specific suite of technologies, but rather, various technologies meant to prevent crashes by detecting a conflict, alerting the driver, and automatically applying the brakes. A complete set of technologies that make up a CAS could be, for example, collision-warning system (CWS) to identify the obstacle, dynamic brake support (DBS) to begin brake assistance, and autonomous emergency braking (AEB) to autonomously apply the brakes without passenger input. However, these are not the sole technologies meant to prevent crashes and improve safety. Based on a study by the National Transportation Safety Board (NTSB) [30], vehicles equipped with the previously mentioned CAS (CWS, DBS, and AEB) could prevent 82.2% of fatalities caused by crashes involving one car striking the rear of another, assuming a 100% market penetration rate of CAVs. As of late 2014, 41.2% of new passenger vehicle models were offered with an optional CAS, while less than 1% of passenger vehicle models came with CAS as a standard feature [30]. However, the technology is becoming more widely available as vehicle technology advances, as only 11% of new passenger vehicles in 2010 came with optional CWS, the most basic technology of the CAS suite laid out previously.

Najm et al. [31] found that some V2V applications in CAVs can help reduce light-duty vehicle crashes substantially. In their paper, they make the claim that 76% of crashes are due to driver error, with the remaining crashes being split between vehicle issues (1%), weather issues (2%), and crashes with no critical reason (21%). Additionally, the vast majority of passenger vehicle crashes occur on straight, dry road surfaces with no adverse weather during the daytime [31]. Major contributing factors to passenger vehicle crashes are various road violations, such as improper lane changing or running a red light (27%), driver distraction (13%), obscured vision (8%), speeding (2%), and alcohol use (2%). Based on these numbers, it is clear that CAVs equipped with the proper technology can prevent many of these types of crashes. Some applications, such as Forward Collision Warning (FCW), Blind Spot Warning (BSW) and Lane Change Warning (LCW), were also found to be all that is needed to prevent crashes previously attributed to human error, thus immediately eliminating 76% of passenger vehicle crashes in a system with a full CAV market penetration. Unlike the CAS suite, FCW, BSW, and LCW are not yet available in passenger vehicles. However, that is expected to change, as experts are calling for car manufacturers to bring technologies such as FCW to their vehicles as soon as possible [32].

CAV Infrastructure Placement

In order to properly plan for an urban CAV system, attention must be paid to the location and placement of roadside units (RSUs), which collect and transmit data to

CAVs. Costs of these units have naturally decreased over time as the technology becomes more advanced and available, but there have been varying reports of their cost per unit in that timeframe. From a 2013 estimation, roadside units could be priced at \$13,000-\$15,000 per unit with a per annum \$2,400 per unit in maintenance [33], though federal-aid funding may be available to cover the yearly maintenance costs [34]. A 2014 source cited a cost of just \$3,200 per unit [35]. Cost, of course, is variable depending on many factors. Location, type of connection (LAN or wireless), and amount of additional features can cause the cost of RSUs to rapidly increase. In terms of the type of connection, LAN is much cheaper than wireless. The cost of a connection system can be reduced depending on the density of RSUs. In the case of a network with many RSUs nearby one another, just one unit is needed to be connected wirelessly – nearby RSUs can be connected by LAN to one another, thus substantially reducing the per unit cost of RSUs in a system where there is an abundance of units [36]. As CAVs enter the mainstream and market penetration starts to increase, infrastructure will certainly become cheaper per unit.

In terms of coverage, RSUs must be placed within 300m of an intersection in order to be effective at communicating with high-speed vehicles [36]. This radius ensures that two vehicles approaching the intersection will be able to communicate their location, speeds, direction, and other parameters to the RSU in order to prevent an incident at the intersection. Too small of a transmission radius could lead to inefficient transfer of information, in the sense that the vehicle may not have time to process the information

and change its trajectory accordingly to keep traffic moving smoothly. In order to adequately cover urban corridors, there must be a slightly larger transmission radius for nearby RSUs. Urban corridors require a higher radius, because the importance of each RSU to correctly transmit and collect information increases as a system becomes more urban – owing to the fact that more vehicles use a particular intersection the more urban it is, and the RSU is thus in charge of keeping more drivers safe. A transmission radius of 300m is thus recommended for extreme urban intersections in order to provide adequate overlap in case one RSU in the system loses functionality [37], but of course, this number varies with the system in question's level of density.

The relationship between cost and coverage is a variable one. The obvious conclusion would be that in order to maximize safety gains, the widest coverage possible is necessary, even if the cost is high. However, due to constant upkeep and maintenance costs, equipping a system with a denser network of RSUs can see large increases in costs with only marginal increases in coverage. In one case, the cost only increases by about 24% if the RSU coverage increases from 20% to 80%, whereas the cost grows by 66.3% when the RSU coverage increases from 80% to 100% [36].

The result that efficiency gains do not increase proportionally to number of units is found again when considering the data-collecting ability of RSUs. In a simulation that tested the efficacy of varying numbers of RSUs, it was found that the units do not see a substantial increase in data-collecting efficiency even when the units per mile of

roadway increased by more than four times [36]. What matters more than number of units in the case of data collecting is the length of time between data collection intervals. For example, 11 units on 11.2 miles of roadway collecting data at intervals of 5 minutes had nearly the same fitness estimation as 48 units collecting data at intervals of 1 minute along the same length of roadway [38]. At a potential cost of more than \$10,000 per unit for installation and maintenance, an extra 37 units collecting information 5 times as often generates a much higher cost without a much higher level of efficiency.

Cost is an important factor when considering how much infrastructure is need in a CAV system. Since it is public agencies and municipalities who are likely to be footing the bill for transportation infrastructure improvements, mitigating costs is a necessary tactic. Even though safety as a goal is nearly unparalleled when considering infrastructure implementations, the budgetary aspects of those improvements are a factor that cannot be overlooked. When a System A can reach 95% efficiency of System B at a quarter of total units and a fraction of the price, government agencies are likely to pursue the cheaper option.

This paper will consider the previously stated option for its infrastructure placement. Roughly one RSU per mile operates at 95% efficiency of the proposed scenarios, and is much more cost effective. This scheme, if widely deployed, would benefit low-budget cities most because of its cost efficiency. However, the “one-unit-per-mile” metric is

based on a grid deployment. In the case of a linear corridor, like Lamar Blvd, it is best to fall back on the transmission radius of 300m as a recommend placement scheme.

The Effect of Penetration Rate

Capacity, travel times, VMT, number of incidents, and many other factors are affected by the penetration rate of connected vehicle technology. In sum, a higher penetration rate of vehicles with connected vehicle technology on a roadway means a) higher capacity, b) shorter travel times, c) typically lower VMT, and d) fewer incidents. The difference between a high and a low penetration rate can lead to substantially different results. For example, low penetration rates can see almost negligible improvements in some of the factors mentioned above:

At low penetration rates, such as if 1 percent of all vehicles on a highway segment are AVs, the highway capacity and congestion reduction benefits will likely be none to very little, except that the presence of AVs in traffic, even if sporadic, may influence other travelers' decisions to purchase AVs in the future. It is also likely that in the early stages with a low presence of AVs in traffic streams, other drivers might prefer greater-than-normal spacing from AVs (due to potential safety-related perceptions) [39].

Even vehicles equipped with just one aspect of connected vehicle technology can have strong impacts on overall network flow. Simply adding cooperative adaptive cruise control (CACC) can have benefits for the roadway. CACC is a system which uses V2V and V2I communications to talk to nearby equipped vehicles and generate automated

responses that occur much more quickly than humanly possible, allowing equipped vehicles to safely travel closer together and thus increasing the road capacity [40]. A 65mph freeway has a capacity of about 2,200, but when 50% of the vehicles are equipped with CACC that number jumps to 2,700. A freeway with 100% of its vehicles equipped with CACC can see a capacity of almost 4,000, which means that congestion-related issues would be nearly cut in half, cutting travel times down significantly [41]. In addition to travel time and capacity improvements, CACC has the ability to cut down on the number of crashes, because it a) intelligently routes vehicles at a safe yet autonomously manageable distance from other cars, and b) has the ability to engage the vehicle's braking systems at a faster reaction time than humans.

Forward Collision Warning (FCW) is another connected vehicle technology that has the potential to vastly improve roadway safety. FCW can detect an impending collision and, if the vehicle is equipped, autonomously engage the brakes or swerve the vehicle in order to avoid the collision [42]. A full market penetration throughout the United States of vehicles equipped with just FCW and CACC would result in a net economic savings of more than \$53 billion (repairs, response to crashes, etc.), and save 497,100 functional person-years in the year 2013 alone. Further equipping vehicles with Cooperative Intersection Collision Avoidance Systems, increases those numbers to \$76 billion and 740,000 functional life person-years [43].

Fagnant et al. [44] looked at safety benefits of CAVs at various penetration rates. Based on NHTSA's 2008 claim that 90% of crashes are due to human error coupled with their 2008 claim that 40% of fatal crashes involve driver alcohol or drug use, their paper assumed that CAVs could eliminate 50% of human error crashes at a 10% market penetration rate, and 90% of human error crashes at a 90% market penetration rate. Other crash reduction rates, however, are not included at the market penetration rate level.

Methodology

In order to make a case for infrastructure placement, data must be collected to identify how bad the problem is, and how much is needed to improve it. For this paper, I collected vehicle counts at on Lamar Blvd just north of Hether St. Additionally, I ran travel time runs along the Lamar corridor between Treadwell St and Manchaca Rd. The purpose of the count data is to compare typical peak period counts on Lamar against capacity values in the present day to show the level of congestion. Similarly, the travel time runs were collected in order to analyze intersection delay to see how it can be improved with CAV infrastructure. This paper will look at the data that I collected, in addition to simulation data from CAMPO's 2040 regional transportation model.

Data that I collected, along with data from other sources, will paint the image of Lamar Blvd's present-day traffic condition, and will serve as a "Pre-CAV" Scenario. A future-year scenario will also be analyzed based on 2040 model data. The future scenario will represent traffic conditions in the year 2040, and assume an 80% market penetration rate – which is a typical prediction for CAV market penetration in 2040. Therefore, this paper will look at present-day traffic flow and travel times and view them through a lens of CAV possibilities. Looking at the future will allow an analysis of the corridor if no changes are made between now and 2040. The future scenario will show what Lamar can look like if predictions about market penetration are correct. Using predicted improvements based on market penetration, the future estimated volumes will be

compared against estimated improvements in capacity due to CAV infrastructure. Additionally, improvements in intersection delay due to CAV infrastructure can be attributed to present day travel times in order to show improvements in travel time that result from equipping an intersection with CAV technology.

Lastly, crashes in the study area were examined to determine if that crash would have happened in a CAV environment. Preventable crashes are those determined to have been caused by human error, which is supported by prevention rates based on literature review presented earlier in this paper. Preventable and unpreventable crashes will thus be brought together, and a new crash prevention rate is proposed for the study area based on previous crashes and their causes. However, a caveat of this analysis is that the data shows a very low number of total crashes reported on the corridor: the corridor saw only 20 reported crashes in a 6-year span. Based on the high usage of this corridor, this crash number is extremely low. Whether this is due to a low reporting rate or just a genuinely low number of crashes is unclear.

Case Study: Data Description



Figure 2: Tube Count Location at Intersection of Lamar Blvd and Hether St

Counts were collected along Lamar Blvd just north of Hether St. Tube counters were used to collect the data. They were chosen because they require no on-site monitoring, and can be left alone for days at a time. The tube counters remained in place for a weeklong period, and thus 24-hour counts were collected. These counts were isolated into the AM peak period counts. The initial idea was to collect seven days' worth of counts in order to get a proper representation of a typical week of travel, and to capture how roadway volumes change over different days of the week. Weekend values were collected as well, but primarily just to observe what sort of volumes exist on the

weekend in comparison to the weekday. Weekend counts were not found to be as valuable because the peak period does not exist over the weekend in the same sense that it exists in the commute times on weekdays. Additionally, counts were collected for both the northbound and southbound direction, and divided accordingly.

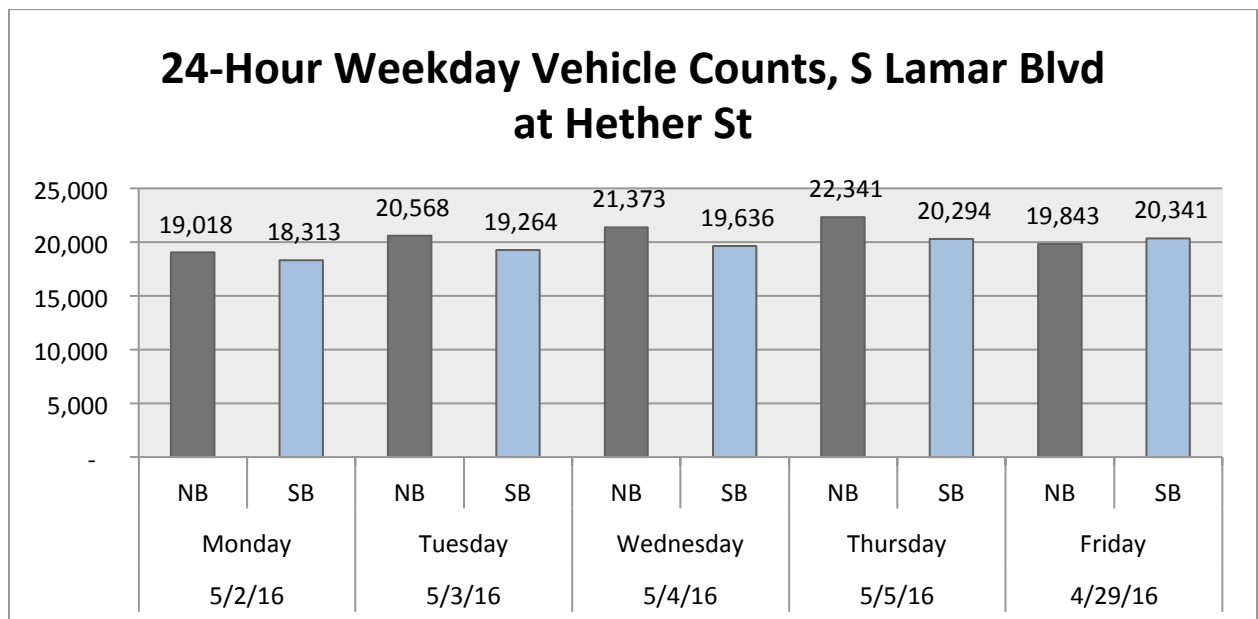


Figure 3: 24 Hour Counts on S Lamar Blvd

Daily counts taken from Lamar Blvd reveal a weekday northbound average of 20,628 vehicles and a southbound weekday average of 19,567 vehicles. For the purposes of this paper, the vehicle counts from Tuesday through Thursday will be used, because they better represent the “average” day, since vehicle trips tend to be more variable on Mondays and Fridays. Therefore, for the purpose of this paper, the northbound direction sees an average of 21,427 vehicles and the southbound direction sees an average of 19,731 vehicles.

This data is important, because this paper will establish metrics that show how CAV technology implementations can affect cars on Lamar Blvd, and the number affected can only be established if the base number of vehicles is accurately collected.

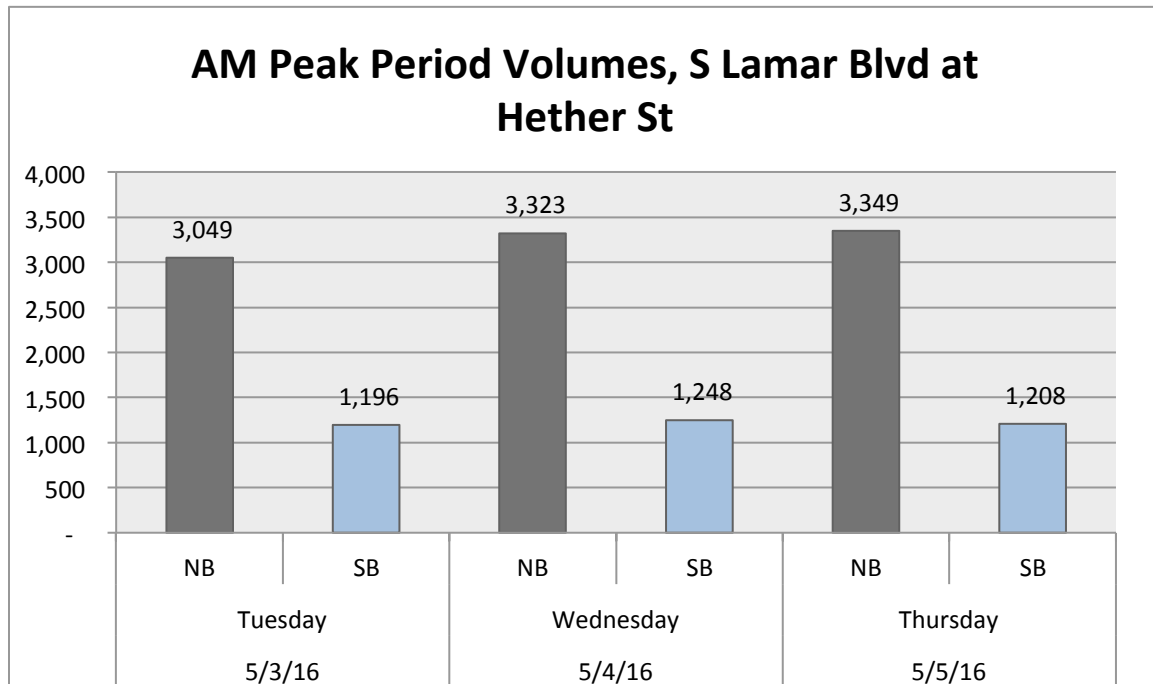


Figure 4: AM Peak Period Counts on S Lamar Blvd

Counts between 7:00 and 9:00 AM were isolated from the 24-hour counts to establish the AM peak period counts. The peak period is the time that the roadway sees the highest usage, and when congestion and crash incidents are typically at their worst. For this reason, the bulk of the analysis of present-day traffic conditions will focus on the AM peak period.

	Average Peak Period	Average Peak Hour
NB	3,240	1,620
SB	1,217	608

Table 1: Average Peak Period and Peak Hour Counts for Lamar Blvd at Hether St

Table 1 above contains information about the average peak period and peak hour counts along Lamar Blvd in 2016. These values are valuable in order to establish a level of congestion for Lamar Blvd. This paper will use these count numbers compared against capacity values laid out by CAMPO's model in order to determine congestion level.



Figure 5: Travel Time Route between Treadwell St and Manchaca Rd

The route between Treadwell St and Manchaca Rd on Lamar Blvd was used for travel time data collection. The route was run during the AM peak period, and in the same timeframe as the count collection: between 7:00 and 9:00AM. The data was collected on a typical traffic day: Tuesday April 12th, 2016. In addition to being recorded on a typical weekday, this data was also collected on a typical month. Since Austin has such a high number of college students, it is important to collect typical traffic data on days when the semester is in session, i.e. avoiding the summer months and the winter break

between December and January. This is done in order to capture Austin as it typically is most of the year – with college students in residence. Data collection outside of the semester risks underestimating true traffic patterns. April falls into the category of a typical month for traffic collection.

Northbound Field Travel Times	
Street Name	Travel Time (sec)
Manchaca Road	--
Bluebonnet Lane	51.1
HAWK Signal	57.2
Oltorf Street	20.1
Hether Street	25.9
Lamar Square	97.6
Treadwell Street	36.4
Avg Total TT (sec)	288.2
Avg Total Intersection Delay (sec)	163.5
Avg Total TT with Intersection Delay (sec)	451.7

Table 2: Average Northbound AM Peak Travel Time and Intersection Delay on S Lamar Blvd

Table 2 above shows the average travel time of the six travel time runs performed on the S Lamar Blvd corridor between Manchaca Rd and Treadwell St in the northbound direction. The table shows the travel time between intersections, but does not include the amount of time stopped. The stop time, or intersection delay, is also included, but as an aggregate average of the six travel time runs. Intersection delay is a product of signal timing as well as congestion –being stopped at a signal adds to intersection delay, as does being stopped behind vehicles when the signal shows a green light. Studies that

estimate the impact of CAV technology on intersection delay will be used along with this data collected.

Southbound Field Travel Times	
Street Name	Travel Time (sec)
Treadwell Street	--
Lamar Square	15.5
Hether Street	43.6
Oltorf Street	18.4
HAWK Signal	8.9
Bluebonnet Lane	35.7
Manchaca Road	32.8
Avg Total TT (sec)	154.8
Avg Total Intersection Delay (sec)	19.3
Avg Total TT with Intersection Delay (sec)	174.1

Table 3: Average Southbound AM Peak Travel Time and Intersection Delay on S Lamar Blvd

Table 3 above shows the average travel time of the six travel time runs performed on the S Lamar Blvd corridor between Manchaca Rd and Treadwell St in the southbound direction. Like Table 2, the intersection delay is included and will be used as a basis for how impactful CAV technology can be to intersection delay, and thus, travel time.

Crash data was pulled from TxDOT's online Crash Records Information System (CRIS) [45]. The Lamar Blvd study corridor was chosen as the location of analysis, and the time period analyzed was the years between 2010 and 2016. The initial intention was to use crashes during the time when counts and travel time data were collected: April and May 2015. However, no crashes were reported in that timeframe. Additionally, single-year crash reports were minimal, with only 4 crashes reported on the corridor in 2016, 3 in

2015, 5 in 2014, 3 in 2013, 3 in 2012, 1 in 2011, and 1 in 2010. Therefore, this paper uses all available crash data that the CRIS provides on the study corridor, which spans between 2010 and 2016. Twenty crash locations on Lamar Blvd in the near vicinity of the study corridor were analyzed. Attributes such as vehicle type, weather condition, and most importantly, cause of crash were looked at in order to determine if the crash could have been prevented in a CAV system.

Lastly, this paper looks at 2040 roadway volumes as projected by the regional Capital Area Metropolitan Planning Organization (CAMPO) model. These projections were made based on expected changes in ingoing and outgoing traffic between today and the year 2040. The CAMPO model takes into account planned new construction in its simulations that produce new traffic flow. This paper uses CAMPO's volume numbers to compare against the proposed capacity after a CAV system is implemented. Data from CAMPO is not however used when analyzing intersection delay or crash reduction, due to the fact that the collected field data was used for those comparisons.

Future Year Penetration Rate and Assumptions

This paper will look at the year 2040 for CAV implementation for a number of reasons. As mentioned previously, a common prediction for the year 2040 is an 80% market penetration rate of CAVs. The year 2040 is significantly far away enough to give the market time to saturate with CAVs, and gives enough leeway if there are hiccups in the market. Furthermore, traffic will undoubtedly be much worse in the year 2040 if the

data challenges prove to be too difficult for CAV technology and as a result causes no changes to be made.

In addition to being a good year for CAV technology impact estimation, 2040 is also the latest projection year for CAMPO's most recent travel demand model. Using CAMPO's data as a basis for CAV technology gives this paper a strong foundation for future year predicted traffic volumes on the Lamar corridor.

Travel time is more difficult to project than traffic volumes, so the analysis of CAV impact on travel times will be reserved for present year field data. This will be valuable in the sense that the analysis can show how impactful CAV technology would be if it were to all of a sudden show up in the present day. Local readers of this paper likely understand how slow traffic can be on Lamar Blvd, and therefore the travel time analysis will be valuable to paint a picture of the real improvements that can be made. Traffic volumes, on the other hand, will be compared against the roadway capacity of the corridor, and therefore is valuable no matter the year of analysis.

It is important to note that simulation-based capacity numbers are not the sole basis for congestion. In reality, there are many more factors that lead to congestion. Bottlenecking, or when traffic demand exceeds roadway capacity, is typically understood to be the cause of just 50% of total congestion. Traffic incidents, work zones, bad weather, and poor signal timing round out the other 50% [46]. Because of this, capacity issues should not be thought of as the sole cause of congestion, but rather

the primary cause. This paper therefore shows the capacity benefits of CAV technology, but it is also true that issues with traffic incidents, bad weather, and poor signal timing would see improvements as well, representing 85% of the causes of traffic congestion.

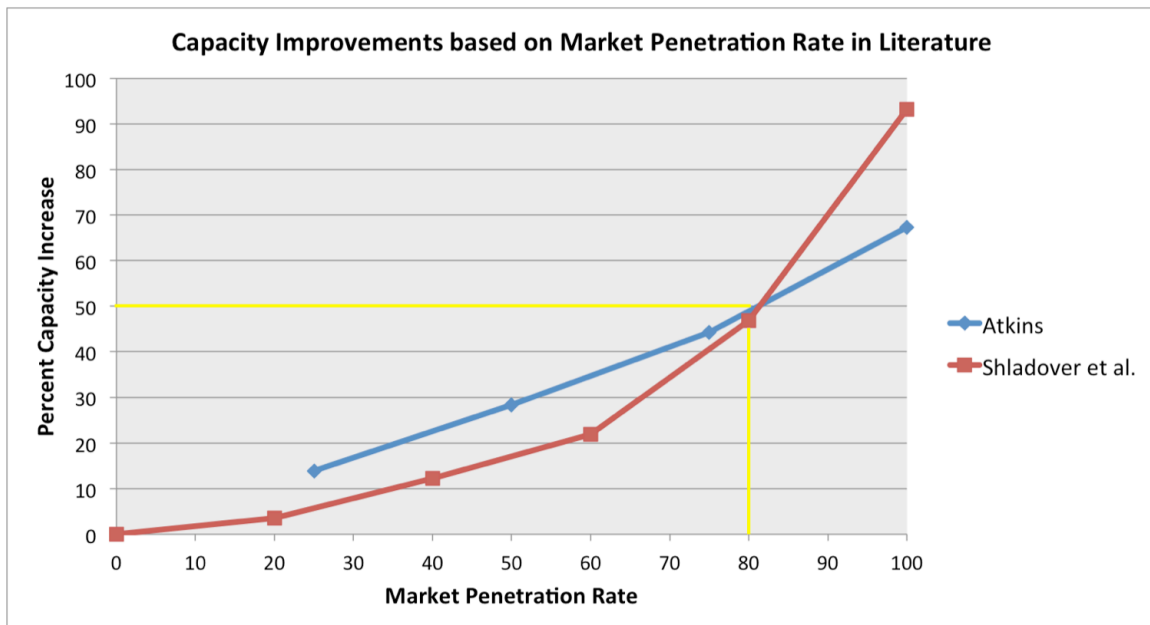


Figure 6: Capacity Improvement Assumptions based on Literature

For this paper's case study, a number of assumptions were made, several of which were drawn from literature. Capacity improvements and crash reduction rates were drawn from reported numbers based on penetration rate, and then transposed linearly to fit the 80% penetration rate used in this study. For example, Atkins [47] reports a capacity increase of 13.9%, 28.3%, 44.2%, and 67.3% at 25%, 50%, 75%, and 100% CAV market penetration rate, respectively. These values correspond to a capacity improvement rate roughly between 47.1% and 53.8% at an 80% market penetration rate. Similarly, Shladover et al. [41] looked at capacity improvement at 10% penetration rate increments, and found a 46.8% capacity improvement rate at 80% market penetration

rate of CAVs. Figure 6 shows the linear capacity improvement rates from each paper, as well as the assumption for this paper in yellow. Additionally, Figure 6 shows that the 80% market penetration rate threshold is the point where the two articles agree, with the Atkins paper assuming a more linear progression of capacity improvement, while Shladover et al assumes a more exponential capacity increase. It was from the two papers in Figure 6 that this paper's 50% capacity improvement rate was drawn.

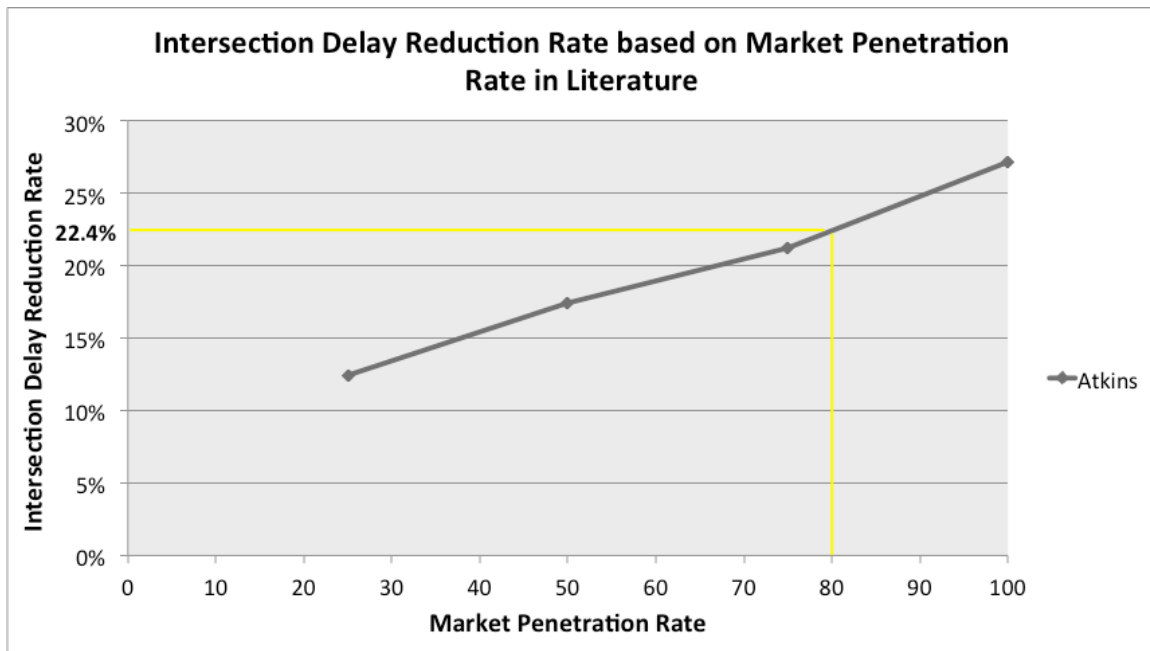


Figure 7: Intersection Delay Reduction Assumptions based on Literature

For this paper, an intersection delay reduction rate was assumed using a similar method as the capacity increase rate assumption. However, the literature was reduced to just one article. The paper by Atkins [47] presents intersection delay at 25%, 50%, 75%, and 100% CAV market penetration rates. From this data, this paper assumes a penetration on a linear scale at the 80% market penetration rate. Based on the data in the Atkins

paper, a 22.4% intersection delay reduction rate can be assumed at an 80% market penetration rate. Thus, this paper will assume intersection delays to be reduced by 22.4% in the Lamar Blvd case study, which will be described later in the paper.

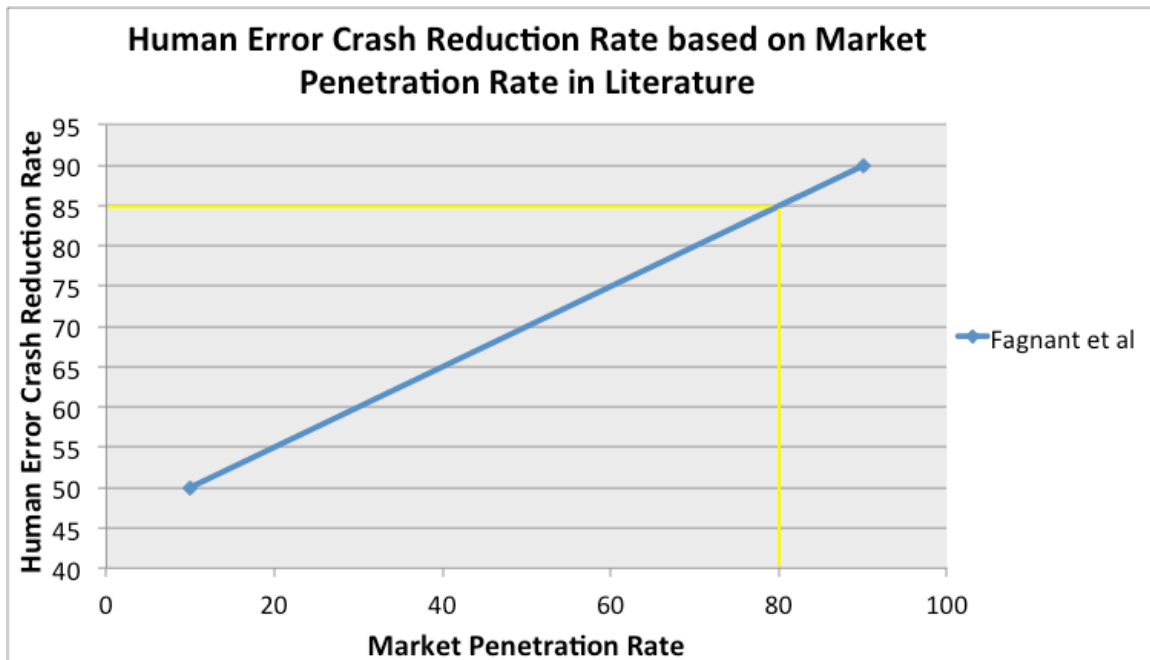


Figure 8: Human Error Crash Reduction Assumptions based on Literature

Safety improvement assumptions were based on Fagnant et al's [44] paper. In their paper, the claim is made that crashes due to human error will be reduced by 50% at just 10% of a CAV market penetration rate. Additionally, the claim is made that 90% of human error-caused crashes can be prevented at a 90% CAV market penetration rate. The paper, however, does not suggest any data points between the two. Therefore, the crash reduction rate used in this paper was assumed on a linear scale from those two data points. Figure 8 shows crash reduction rates at various market penetration rates based on Fagnant et al's paper, and the point at which an 80% market penetration rate

is found. Based on this data, an 85% crash reduction rate is assumed in this paper for all human error-caused crashes in the year 2040.

There has been detailed research on the share percentage of other types of crashes, as noted previously in this paper, but the lack of an associated market penetration rate of CAVs and their impact make it difficult to make an assumption about other crash types. Regardless, this will not pose much of a problem for the case study because the majority of field vehicle crashes were caused by human error. Weather was a factor for one of the field crashes, but there is not significant data about additional potential causes for the crash. The assumption in this paper will therefore be that CAV infrastructure will have no impact on weather-related crashes.

Results: Capacity

This paper will compare 2040 projected vehicle volumes against standard capacity values for the Lamar corridor to determine level of congestion. Capacity improvements due to CAV technology will also be shown and compared against those same 2040 volume numbers to show how much of an impact CAV technology can make on capacity, and thus, congestion. The results will be based on hand collected field data, and projected simulation-based data based on the year 2040. Based on data presented previously in this paper, the benefits of a CAV system are shown in the form of volume to capacity ratios.

Field Data

CAMPO's traffic model has roadway capacity at its foundation. Traffic flow and capacity are primary determiners of congestion on a roadway: if there are more vehicles on a roadway than the capacity allows, congestion will naturally occur because there is simply not enough amount of road to support the number of vehicles. The ratio between volume and capacity is aptly named the Volume to Capacity Ratio, or VC Ratio. Just as congestion occurs when volume exceeds capacity, it can also be said that congestion occurs when the VC Ratio exceeds 1.0. Capacity is typically written as a per-lane, per-hour basis, or vphpl, meaning a roadway capacity of 1,000 vphpl indicates that 1,000 vehicles can fit into one lane in one hour on that roadway without congestion, assuming free flow vehicle speed. Intersection delay and stop time factor into the

equation, but the bottom line is that if there are more vehicles on a road than capacity allows, congestion is unavoidable.

The first metric that needs to be assessed in order to understand the impact of CAV infrastructure is present-day roadway volumes. This data was collected as a result of the field data collection using tube counts. As stated in previous sections, data for the AM peak period was collected, which, in the case of this paper, is considered to last from 7:00AM to 9:00AM.

The peak travel direction in the AM peak period is primarily northbound, due to vehicles commuting into the central Austin region for work. Therefore, the northbound counts are much higher than the southbound counts. Table 1, found earlier in this report, shows that the vehicle volumes on northbound Lamar Blvd amounted to 1,620 vph. The southbound direction only saw 608 vph. Lamar Blvd has 2 lanes at the point of data collection, meaning that the average counts for the area of interest are 810 vphpl in the northbound direction, and 304 vphpl in the southbound direction.

Lamar Blvd is considered to be a major arterial roadway in a very urban part of Austin. Based on these factors, as well as the speed limit of the roadway, Lamar Blvd can support a capacity of roughly 1,600 vphpl. This value is more than double the amount of vehicles counted, but, as stated before, capacity constraints only represent 50% of congestion problems. Assuming a capacity threshold of 1,600 vphpl for the Lamar corridor, the northbound and southbound directions see a VC Ratio of 1.01 and 0.38,

respectively. Vehicle counts do not tell the whole story with respect to congestion – this is why travel times were collected along the corridor as well.

Northbound		
Street Name	Travel Time (sec)	
	Peak	Off-peak
Manchaca Road	--	--
Bluebonnet Lane	51.1	29.9
HAWK Signal	57.2	36.3
Oltorf Street	20.1	10.8
Hether Street	25.9	18.1
Lamar Square	97.6	54.3
Treadwell Street	36.4	15.3
Avg Total TT	288.2	164.9
Avg Total Intersection Delay	163.5	9.1
Avg Total TT with Intersection Delay	451.7	174

Table 4: Comparison of Peak and Off-peak Travel Times along the Lamar Corridor

Table 4 above shows the comparison of peak (7:00AM-9:00AM) and off-peak (1:00PM-3:00PM) travel times collected. The northbound direction, which is the peak direction in the AM period, sees an average of just over 7.5 minutes to traverse the entire corridor during the peak period. However, in the off-peak, the same corridor takes just 2.9

minutes to traverse. These numbers alone are strong evidence of congestion along the corridor.

CAMPO Data

CAMPO's AM 2040 network model contains roadway volumes projected in the year 2040 for the AM peak period. These values are based on expected demographic and employment changes to the region, which is then simulated as vehicle demand in the network. The CAMPO network assumes that planned projects with expected completion dates before 2040 will in fact be completed. Otherwise, the network is the same as the present-day transportation network in Austin.

The information contained within the CAMPO model, while simulation-based, serves the same purpose as the data collected in the field. The 2040 CAMPO model contains lane numbers and future vehicle volumes, which provide the basis of a comparison assuming CAV technology is present.

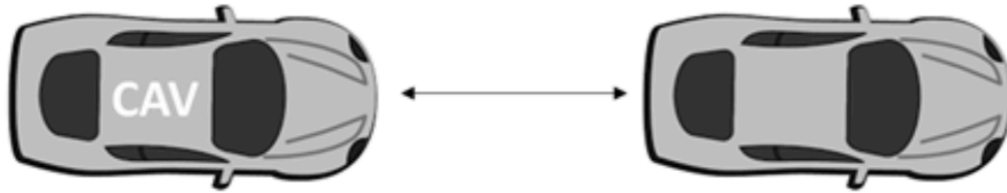
The 2040 CAMPO model shows that an average of 3,689 vehicles per hour will be traveling northbound on Lamar Blvd in the AM peak period, which is just about 1,844 vphpl. This number is more than double the number of vehicles counted in the present day. The southbound direction sees a similar trend – in 2040, the CAMPO model estimates that 2,489 vehicles will be using the roadway segment on Lamar Blvd just north of Manchaca Rd. Split evenly between the two lanes, this amounts to 1,244 vphpl, slightly more than twice the amount of vehicle traffic in the year 2016.

Vehicle volumes will certainly increase in Austin in the time between now and 2040, but capacity will see no change unless a different type of vehicle is used. With a capacity of just 1,600 vehicles on Lamar Blvd, the 2040 volume numbers are unsustainable and will result in a permanent gridlock. The data from CAMPO shows that there will be 244 more vehicles per hour per lane in the northbound direction than the roadway can currently contain, which of course will result in extreme congestion. The southbound numbers, while also high, are still below the standard capacity of 1,600 vphpl. However, the southbound direction's projected volume numbers are roughly 50% higher than present day northbound vehicle volumes. If Lamar's congestion today is any indicator, traffic in both directions on Lamar Blvd in 2040 will be extremely delayed.

CAV Benefits

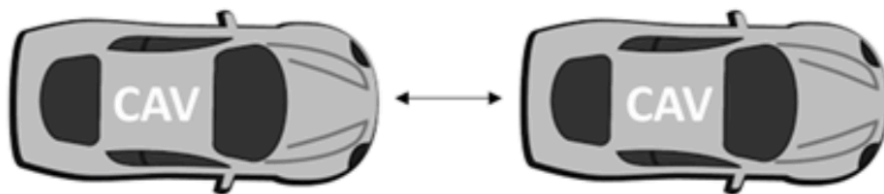
Based on previous research, adequately placed CAV roadside units are bound to engender vast increases in roadway capacity. The amount of increase one can expect from CAV infrastructure necessarily relies on many factors – including penetration rate, level of vehicle connectivity, level of vehicle autonomy, and so on. Much of the relevant literature makes different assumptions about what level of connectivity and autonomy vehicles will have by the year 2040, so a true estimate of capacity improvements will be hard to accurately predict. However, CAV technology is predicted to be very advanced by the year 2040, with many predicted connectivity features being expected to have been introduced by that year.

FOLLOWING LEGACY FLEET VEHICLES



If a CAV is following a legacy fleet vehicle, “normal” following behaviour applies

FOLLOWING OTHER CAVs



If a CAV is following another CAV, different following behaviour can be applied – in this case, a shorter gap

Figure 9: Connectivity and Following Behavior [47]

The largest reason that CAV infrastructure is expected to increase roadway capacity is because connectivity means that CAVs can talk to other CAVs and thus know their movements before human reflexes can react. This means that following distances between CAVs can be shorter, therefore fitting more vehicles on a roadway, as seen in Figure 9. This explains why penetration rate is so important – the higher the percentage of CAVs on the road means that following distances can be much shorter.

Based on a penetration rate of 80%, which assumes a capacity improvement of 50% (see Figure 6), the Lamar corridor should see an increase in capacity from 1,600 vphpl at 0% penetration rate to 2,400 vphpl at 80% penetration rate. The previous section noted that 1,844 vphpl are predicted to use the Lamar corridor in the northbound direction every morning, which is too many for a system with a 0% penetration rate of CAVs (a VC Ratio of 1.15), as it is in the present day. If vehicle technology remains the same in 2040 as it is today, the Lamar corridor will be in a state of constant gridlock in the AM peak period, unless major changes to the roadway network are made. However, at a 50% capacity increase, 1,844 vphpl in the northbound direction and 1,244 vphpl in the southbound direction should be able to traverse the Lamar corridor when 2,400 vphpl are able to fit, at a VC Ratio of 0.77 and 0.52 in the northbound and southbound direction, respectively. There is sure to be some level of congestion, as only 50% of congestion is caused by a lack of capacity, as cited earlier in this paper. Future-year congestion will be worse than present day if no CAV-related changes are made, but significant progress can be made at an 80% penetration rate of CAVs. Congestion should be much less of a problem on Lamar Blvd in the year 2040 if an 80% penetration rate becomes a reality.

Results: Travel Time and Intersection Delay

Changes in travel time for future years can be difficult to pretend, as the time it takes to traverse a corridor is even more variable than the average number of vehicles using a corridor. Therefore, this paper will look at predicted improvements to intersection delay that CAV infrastructure can engender. The collected field travel times will serve as the basis for analysis.

As presented in Tables 2 and 3, travel times along the Lamar corridor are variable in the AM period. The northbound direction is undoubtedly more congested in that period than the southbound direction. Additionally, intersection delay is much higher in the northbound direction than the southbound. The moving time will surely improve with an addition CAV infrastructure, but the impact is hard to predict. However, there have been papers written about improvement to intersection delay that can be quantified.

In the northbound direction, 288.2 seconds of the total 451.7 seconds are spent in moving traffic, while the remaining 163.5 seconds (36.2% of total travel time) are spent either stopped at an intersection, or behind other vehicles that are stopped at an intersection. Based on literature (see Figure 7) [47], a 22.4% intersection delay reduction will be assumed at the 80% market penetration level. That level of delay reduction means that the 163.5 seconds of intersection delay in the collected field data would be reduced to 126.9 seconds of intersection delay, shaving nearly 40 seconds off of the trip down Lamar corridor. Thus, travel time in the northbound direction during

the AM peak period on the Lamar corridor would be reduced from 451.7 to 415.1 seconds if CAV infrastructure were implemented in present day and an 80% market penetration rate of CAVs existed.

In the southbound direction, only 19.3 seconds of the total 174.1 seconds of travel time in the AM peak period were attributed to intersection delay. Based on the same intersection delay reduction percentage of 22.4%, that amount of intersection delay would be reduced to 14.9 seconds, only losing 4.4 seconds of total travel time. This impact is minimal, and goes to show how much more impactful CAV technology can be when congestion is more extreme.

Results: Safety

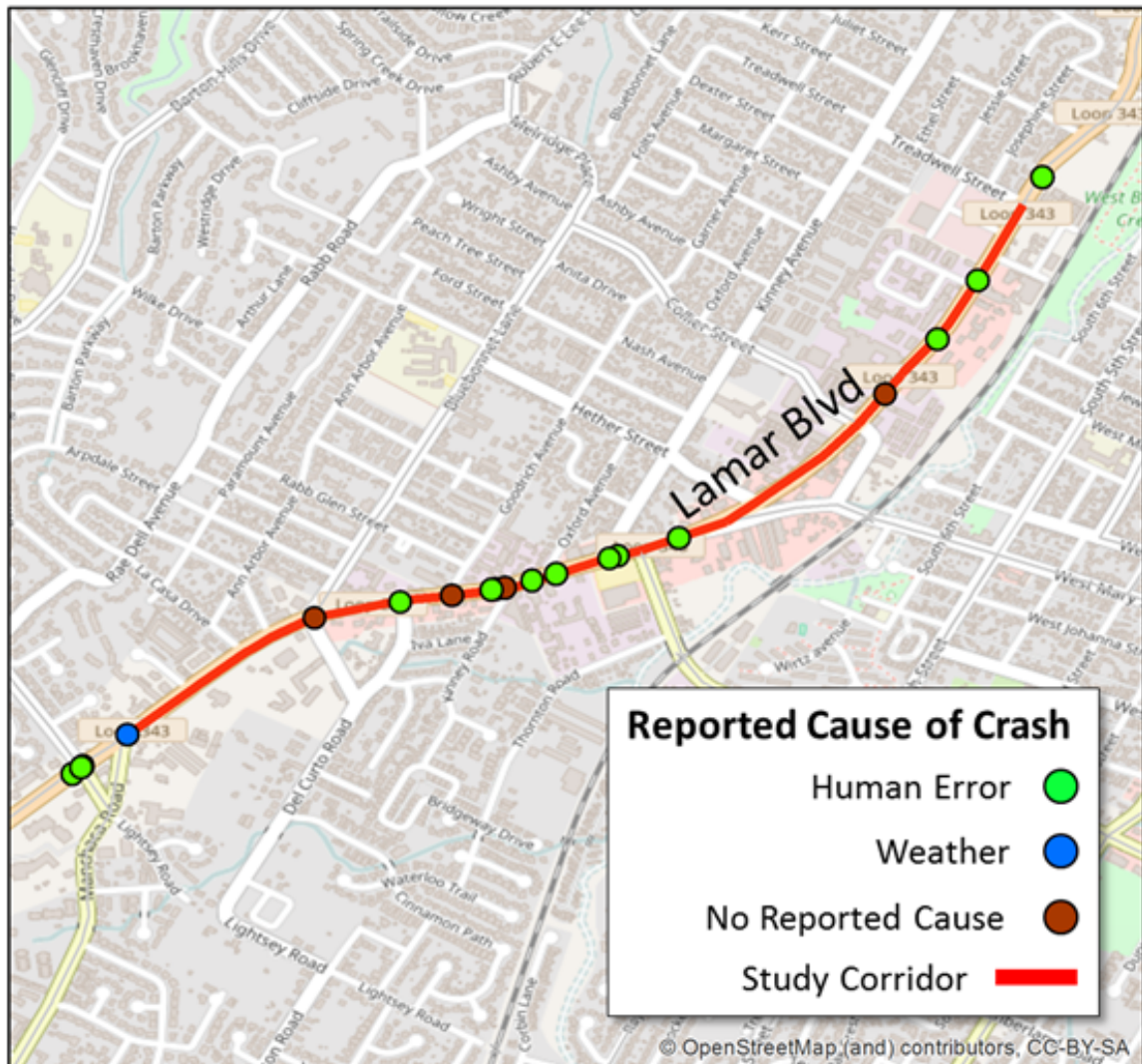


Figure 10: Crash Locations on the Study Corridor and Reported Cause

A total of 20 crashes occurred in the near vicinity of the study corridor between the years of 2010 and 2016 (the full table can be found in the Appendix). The cause of each crash was not necessarily explicit in the crash data. Rather, a “manner of collision” was included: the angle of each vehicle and the direction in which the vehicle was moving. Other information related to the crash was included, such as whether the crash was

related to a vehicle entering or exiting a driveway, whether the crash occurred in slow-moving traffic, whether a vehicle was changing lanes when the crash occurred, and so on. Based on this information, the cause of the crash was assumed. The goal of this analysis was to assume crash cause among human error, weather, and other factors, and then apply crash reduction rates rooted in literature to the human error-based crashes. The benefit to the case study is a crash reduction rate that can be tentatively applied to this stretch of corridor, if a CAV system is introduced at an 80% market penetration rate.

Of the 20 crashes, three were explicitly stated as having been caused by “attention diverted from driving.” These are immediately ruled as having been caused by human error. Only one crash is listed as having been caused by a vehicle changing lanes. This, too, can be attributed to human error, as a CAV with Lane Change Warning (LCW) would prevent itself from making this error. A major indicator that provided the assumption of human error was the manner of the direction of the collision – if two vehicles were moving in the same direction, it was assumed that the crash was a rear-end collision and could have been prevented by Forward Collision Warning (FCW) on an equipped CAV. Of the 20 crashes, 9 of them involved two vehicles moving in the same direction, of which 3 of the previously mentioned crashes (2 diverted attention, 1 vehicle changing lanes) are included. Of the 9 same-direction crashes, 5 are listed as “one straight-one stopped,” 2 are listed as “both going straight-rear end,” 1 is listed as “both going straight-sideswipe,” and 1 is listed as “one straight-one left turn.” All of these are assumed to be

caused by human error, whether by the vehicle crashing or by the vehicle being crashed into. The 5 “one straight-one stopped” crashes indicate a vehicle unable to slow itself before colliding with a stopped car, and the 2 “both going straight-rear end” indicate a vehicle traveling too fast to prevent itself from hitting the back of another car. The single entries of “both going straight-sideswipe” and “one straight-one left turn” indicate inattention or a visibility issue on the part of one of the drivers. This totals to 10 crashes: 3 crashes explicitly stated as being caused by diverted attention, 1 crash explicitly stated as being caused by a vehicle changing lanes, and 6 remaining crashes assumed based on the direction of the conflict. All of these incidents could be prevented by FCW, in theory, and can be attributed to human error.

Of the remaining 10 crashes, 4 crashes were associated with a vehicle entering or leaving a driveway. Most new vehicles manufactured today come equipped with back-up cameras, which would seem to be crucial in these driveway collisions. If the offender instead collided with a vehicle in front of it slowly entering a driveway, this could have been prevented by FCW. Regardless, driveway collisions are likely associated with human error – crashes involving drivers who were unable to swerve or backup in time due to inattention or slow response time would be prevented by vehicles that can speak to one another and know the trajectory and location of one another. Therefore, these 4 crashes can also be attributed to human error, bringing the total to 14.

Finally, 1 crash only involved one motor vehicle, but an additional factor was listed as “swerved or veered-avoiding vehicle stopped or moving slowly in traffic lane.” Whether this crash was caused by the stopped or slowly moving vehicle in the traffic lane, or the vehicle that crashed into it, this one can also be attributed to human error. This is the final crash that is assumed to be attributed to human error, which brings to the total to 15 out of 20 crashes.

The remaining 5 reported crashes have ambiguous causes. All 5 lack information in the “other factor” column. Two of the crashes involved two vehicles moving in opposite directions, 2 involve just one motor vehicle turning left, and the final crash involves an angle crash where both vehicles were moving straight. Due to a lack of information, none of these can be assumed to be caused by human error. However, the weather condition is included in this data, and one of the 5 crashes occurred on a rainy day. The only possible assumption that can be tied to this crash is weather-related, and thus certainly not caused by human error.

At a 100% market penetration rate, it can be assumed that 100% of human-error crashes can be prevented, due to every vehicle in the system having the capability of communicating with one another and pre-emptively preventing crashes, assuming there is no technology failure.

As stated earlier (see Figure 8), a CAV system with an 80% market penetration rate can prevent only 85% of human-error crashes. Based on this crash reduction rate, the 15

crashes on Lamar Blvd that were caused by human error would be reduced to 2.25, which would be rounded down to just 2 crashes. There can be no assumption made about the cause of the other 5 crashes, so those will remain as unpreventable in this model. That results is a total of 7 crashes, down from 20 crashes in a system with no CAVs. Thus, 13 out of 20 crashes can be prevented in a CAV system with an 80% market penetration rate, leading to a crash prevention rate on the Lamar corridor of 65%. However, the small sample size of crashes makes this number unreliable until further testing on a larger sample can be done.

Results: Infrastructure Placement and Cost

Earlier in this paper, an allocation scheme of one unit of CAV infrastructure per corridor mile was recommended, based on efficiency and cost measures. While estimations on cost per unit are variable, the majority of predictions fall between \$3,000 and \$15,000 per unit. The inclusions of federal subsidies to fund maintenance and installation may bring the cost down, and with the assumption that subsidies will exist, the cost per unit will likely be on the lower end of the range previously mentioned. Therefore, this paper will assume a cost of \$5,000 per unit.

The Lamar Blvd corridor between Treadwell St. and Manchaca Rd. measures to roughly 1.5 miles in length. At one unit per mile, the Lamar Blvd corridor will require at most just 2 RSUs. However, the placement recommendation in literature is based on a grid, not a linear corridor. Rather, this paper will recommend an allocation scheme that is based on the assessment that there need to be enough infrastructure to cover a radius of 300m per unit. With only 2 RSUs on the 1.5-mile (2,414 meter) corridor, the 300m-coverage minimum would not be met. Therefore, this paper will recommend 8 units to cover the corridor. At \$5,000 per unit, the total cost would be \$40,000 for the 1.5-mile Lamar corridor.

As a comparison, the cost to re-stripe a roadway is about \$6,367 per mile at an average of \$1.21 per foot [48]. At that rate, the entire 1.5-mile Lamar Blvd corridor would cost roughly \$9,550 to re-stripe. This amount is 24% of the cost to equip the same stretch of

roadway with CAV infrastructure, showing that it can be comparatively inexpensive to fund CAV infrastructure projects.

Conclusion

CAVs have the capability to vastly improve transportation systems, even at small scales. Cities without the capital typically necessary to fund major infrastructure projects could theoretically fund pilot projects with CAV infrastructure fairly cheaply, at just over \$16,500 per mile. In order for technology to reach the point where this is all possible, consumers will have to widely accept CAVs to an 80% market penetration rate – which is no small task. There are many issues that the technology will have to overcome in order to prosper, including a myriad of data aggregation, privacy, and transmission concerns. Regardless, with recently proposed federal transportation rules, we may see CAV technology required on 25% of new vehicles produced in the year 2020, and the tech required on 100% of new vehicles by 2023 [49]. That gives consumers a short window of time to accept CAVs as the car of the future, and it gives automotive companies an even smaller window of time to overcome issues that may plague the technology.

The primary cited benefit of CAV systems is the vast reduction of crashes and overall improvement of safety associated with cars appropriately equipped with the technology. Literature states that 85% of crashes can be prevented at the 80% market penetration rate. Vehicle features already present as of 2017 are already working to prevent crashes – features such as adaptive cruise control, automated braking systems, and automatic emergency assistance. These technologies will evolve and mature as CAVs fall more and more into the mainstream. As the technology advances, so too will

crash prevention methodologies advance. Propagation of CAV technology will only make roads safer if used appropriately.

Efficient infrastructure placement is a key aspect to ensure that CAVs are communicating effectively. There is a scale on which CAV infrastructure can be implemented: from a minimum threshold density needing to be met, to abundant infrastructure for maximum communication. Planning agencies may want to implement infrastructure frugally, with minimum costs for the minimum baseline efficiency standards. By looking at the Lamar Blvd corridor, this paper has established what that baseline could look like for the city of Austin.

Capacity and travel time can see major improvements via CAV infrastructure. This paper has shown what a large market penetration rate of CAVs can do for corridor capacity. Present-day vehicle volumes are handled to an extent by Lamar's capacity as a major arterial, but CAMPO data has shown that the projected volumes for the same corridor will exceed roadway capacity by the year 2040. An influx of CAVs is shown to increase the capacity of the Lamar corridor to a point where it can handle the increased amount of traffic. Similarly, intersection delay sees a decrease in a CAV-heavy vehicle system. The effect of CAVs on intersection delay is seemingly minimal, but an increased roadway capacity should contribute to an overall decrease in travel time. Crashes, too, can be widely prevented, seeing as the majority of reported crashes on the corridor were caused by human error – which is the CAV's strong suit in crash prevention.

Based on the analysis in this paper, a system with 80% penetration of CAVs is expected to engender a 50% capacity increase – in the case of Lamar Blvd, this rate of capacity increase helps congestion by bringing the VC Ratio down from oversaturation (>1.00) to manageable numbers. Intersection delay, too, sees a slight improvement in a CAV system. A 22.4% decrease in intersection delay could potentially help corridors with high congestion and travel times. This was shown to help in the heavily congested northbound direction of Lamar Blvd, but the southbound direction of Lamar Blvd saw less of an impact due to its relatively smoother traffic flow. This paper also made an argument for crash reduction due to CAVs. The analysis found that 65% of crashes on the 1.1-mile Lamar Blvd corridor between 2010 and 2016 would have been preventable in a system where 80% of vehicles have connected-autonomous capabilities. While the crash sample was small, and the crashes included no fatalities, this crash reduction rate would drastically reduce death and injury on urban corridors.

CAV infrastructure may be a relatively economical way to ease traffic congestion once the technology is available. The Lamar corridor in Austin, Texas is already heavily congested, and will only get worse if no large changes are made to the roadway network. Austin's congestion is among the worst in the state, and it certainly isn't getting any better. CAV infrastructure is an alternative to typical congestion-relieving methods, such as build outs of new roadways, lane expansions, and so on. With consumers footing the majority of the bill on the move to CAV technology, cities would be right to follow suit. The federal government supports the advancement, with

mandates to manufacturers and potential subsidies for infrastructure maintenance. As long as the technology can get over its growing pains, the benefits it brings to safety and congestion alone make it an attractive option for all future roadways.

Appendix

Crash ID	Manner of Collision	Other Factor	Weather Condition	Cause Judgment
14572734	Angle - Both Going Straight	Not Applicable	Clear	Other
12840818	Angle - Both Going Straight	One Vehicle Leaving Driveway	Clear	Human error
13408695	Angle - One Straight-One Left Turn	Attention Diverted From Driving	Clear	Human error
12596722	Angle - One Straight-One Left Turn	One Vehicle Leaving Driveway	Clear	Human error
14067156	One Motor Vehicle - Going Straight	One Vehicle Leaving Driveway	Clear	Human error
11464968	One Motor Vehicle - Going Straight	Swerved Or Veered-Avoiding Vehicle Stopped Or Moving Slowly In Traffic Lane	Clear	Human error
15661723	One Motor Vehicle - Turning Left	Not Applicable	Clear	Other
12543946	One Motor Vehicle - Turning Left	Not Applicable	Clear	Other
14181995	One Motor Vehicle - Turning Right	One Vehicle Entering Driveway	Clear	Human error
15234645	Opposite Direction - One Straight-One Left Turn	Not Applicable	Rain	Weather

12793431	Opposite Direction - One Straight-One Left Turn	Not Applicable	Clear	Other
13389503	Same Direction - Both Going Straight-Rear End	Attention Diverted From Driving	Clear	Human error
14113849	Same Direction - Both Going Straight-Rear End	Slowing/Stopping-For Traffic	Clear	Human error
14282459	Same Direction - Both Going Straight-Sideswipe	Vehicle Changing Lanes	Clear	Human error
14868079	Same Direction - One Straight-One Left Turn	One Vehicle Entering Driveway	Clear	Human error
14979625	Same Direction - One Straight-One Stopped	Attention Diverted From Driving	Clear	Human error
14329935	Same Direction - One Straight-One Stopped	Construction - Within Posted Road Construction Zone (Not Related To Crash)	Clear	Human error
13626773	Same Direction - One Straight-One Stopped	Slowing/Stopping-For Pedestrian, Pedalcyclist, etc. In Road	Clear	Human error
14787161	Same Direction - One Straight-One Stopped	Slowing/Stopping-For Traffic	Clear	Human error
13224489	Same Direction - One Straight-One Stopped	Slowing/Stopping-To Make Left Turn	Clear	Human error

Table A.1: Crashes on Lamar Blvd and their Assumed Cause

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